# Learning Autonomous Vehicle Safety Concepts from Demonstrations

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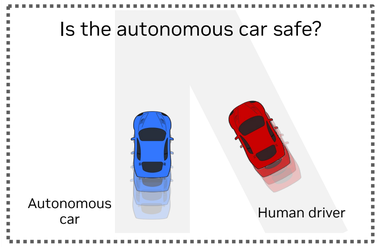
## On the importance of having an independent safety evaluation module




Within the AV stack, there typically is a prediction model that predicts the behaviors of other agents, and a planner that uses the prediction model to make informed decisions. However, the prediction model is not always accurate, and the planner may not respond fast enough to split-second threats.

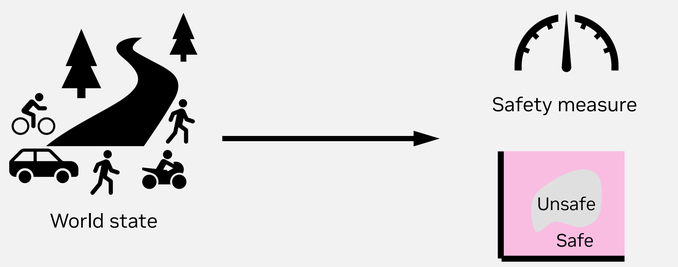
Therefore, there needs to be an independent safety module that can intervene with a safe maneuver anytime upstream components "make a mistake". But *when* should such a safety module intervene, and *how* should it do so?

## What exactly is a "Safety Concept"?

First, we define some terminology to describe what our goal is.

Two functions mapping from world state to:

1. Safety measure
2. Set of allowable safe controls




Examples:

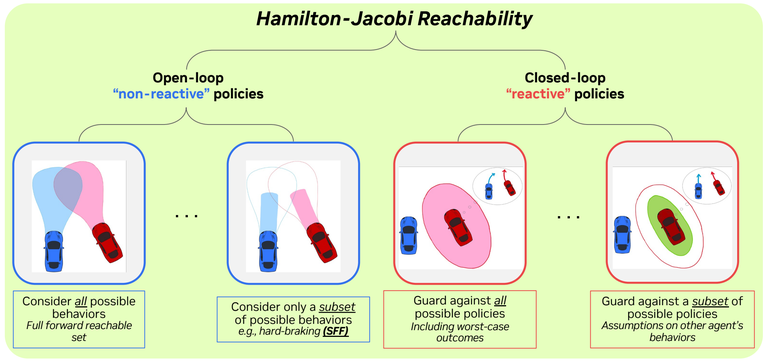
- Velocity obstacles
- Safety Force Field
- Responsibility Sensitive Safety
- Forward reachability
- Backward reachability

## How can we synthesize a novel safety concept?

We can describe a family of safety concepts via HJ reachability

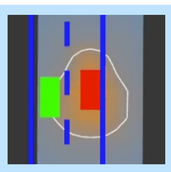
Hamilton-Jacobi-Isaacs partial differential equation (Robust HJB equation)

$$\frac{\partial V(x,t)}{\partial t} + \min\left\{0, \max_{u\in U}\min_{d\in D} \frac{\partial V(x,t)}{\partial x}\cdot f(x,u,d)\right\} = 0$$
$$V(x,0) = v(x)$$



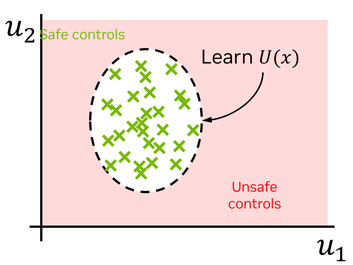

By varying the parameters of the HJ reachability problem, we can describe both closed-loop and open-loop behaviors, and anything in between.

## How should we select "reasonable" control bounds?



Picking *all possible* controls & disturbances leads to overly conservative safety concepts

Given a dataset of states and controls: $(x^{(1)}, u^{(1)}), (x^{(2)}, u^{(2)}), \ldots, (x^{(N)}, u^{(N)})$ we want to learn $U(x)$




**Key insight**: Humans take controls that keep them safe. Taking controls outside the boundary will lead to an undesirable outcome.

Data lives inside a control invariant set.

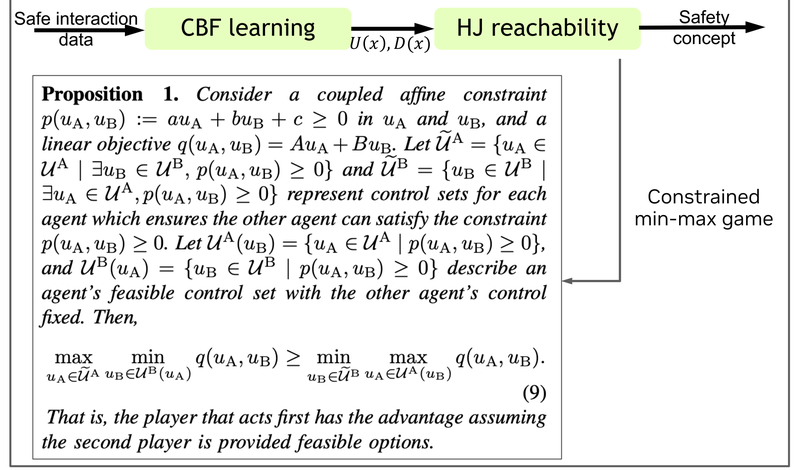
## Control set learning via Control Barrier Functions

$$\max_{u\in U} \underbrace{\nabla b(x)^T f(x,u)}_{\dot{b}(x)} \geq -\alpha(b(x)) \quad \forall x \in X$$

Learn parameters of $\alpha$ so that this condition holds for the dataset

Bound the rate at which the system approaches the boundary

## How do we account for the constraint coupling when synthesizing a safety concept with HJ reachability?




**Proposition 1.** *Consider a coupled affine constraint* $p(u_A, u_B) := au_A + bu_B + c \geq 0$ *in* $u_A$ *and* $u_B$*, and a linear objective* $q(u_A, u_B) = Au_A + Bu_B$*. Let* $\widetilde{\mathcal{U}}^A = \{u_A \in \mathcal{U}^A \mid \exists u_B \in \mathcal{U}^B, p(u_A, u_B) \geq 0\}$ *and* $\widetilde{\mathcal{U}}^B = \{u_B \in \mathcal{U}^B \mid \exists u_A \in \mathcal{U}^A, p(u_A, u_B) \geq 0\}$ *represent control sets for each agent which ensures the other agent can satisfy the constraint* $p(u_A, u_B) \geq 0$*. Let* $\mathcal{U}^A(u_B) = \{u_A \in \mathcal{U}^A \mid p(u_A, u_B) \geq 0\}$*, and* $\mathcal{U}^B(u_A) = \{u_B \in \mathcal{U}^B \mid p(u_A, u_B) \geq 0\}$ *describe an agent's feasible control set with the other agent's control fixed. Then,*

$$\max_{u_A\in\widetilde{\mathcal{U}}^A} \min_{u_B\in\mathcal{U}^B(u_A)} q(u_A, u_B) \geq \min_{u_B\in\widetilde{\mathcal{U}}^B} \max_{u_A\in\mathcal{U}^A(u_B)} q(u_A, u_B). \quad (9)$$

*That is, the player that acts first has the advantage assuming the second player is provided feasible options.*

## What does a data-driven safety concept look like and what does it mean?